DYNAMICALLY LEVERAGING THE LOW-VOLATILITY EFFECT

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Abstract
We present a dynamic approach to managing the market beta of low-volatility portfolios. By applying machine learning-based forecasts to estimate the probability of significant market losses, we adjust the beta of low-volatility portfolios in response to changing market conditions. When the probability of market losses is low, we increase beta to one through leverage. Conversely, during periods of heightened market stress, we reduce beta or hedge exposure to preserve the downside resilience of low-volatility portfolios. Empirical evidence from European markets shows that this approach enhances returns while preserving the defensive characteristics of low-volatility portfolios. It outperforms traditional low-volatility strategies and those with a fixed target beta of one and can also be extended to other defensive strategies, such as multi-factor portfolios, to further improve their risk-return profiles.

1. INTRODUCTION

One of the most intriguing anomalies in financial literature is the observation that stocks with lower volatility have historically outperformed stocks with higher volatility. This runs counter to a core principle in finance and traditional asset-pricing-models such as the Capital-Asset-Pricing-Model (CAPM) which asserts that greater risk is rewarded with higher expected returns. As low volatility portfolios have historically experienced high risk-adjusted returns and lower drawdowns compared to a capitalization-weighted benchmark, low-volatility has become a popular investment style that has gained traction not only in literature but also among practitioners. The low-volatility effect can be partly explained by limits to arbitrage, which arise from factors such as benchmark constraints, leverage aversion, and short-selling restrictions faced by institutional investors. Additionally, behavioral biases such as lottery-preference, where irrational investors overvalue highly volatile stocks with little chance of significant gains in the hope of big profits, and overconfidence, which leads investors to overpay for speculative stocks, further inflate the prices of high-volatility stocks. As a result, high-volatility stocks tend to deliver lower future returns compared to their low-volatility counterparts (Baker, 2011).

While low-volatility as a factor is appealing to investors for its relatively high returns and lower risk over long periods of time, it does also come with some characteristics that present opportunities for improvement. Due to its defensive nature and hence lower market beta, low-volatility portfolios tend to underperform during strong upside markets. To enhance the performance of the low-volatility effect, Blitz et al. (2024) applies a constant leverage to a low-volatility portfolio to boost its beta to one and demonstrate that their approach yields to higher returns comparing to an unlevered low-volatility portfolio but aligns its risk-profile more closely with the broad equity market. In this whitepaper, we propose a dynamic approach to managing the market beta of low-volatility portfolios. Our strategy increases market exposure during stable, upward-trending markets, when low-volatility portfolios tend to underperform the broader equity market. Conversely, during periods of market stress, we utilize the defensive beta of low-volatility portfolios or even hedge it to reduce sensitivity to market fluctuations. To achieve this, we apply an innovative model that integrates machine learning-based forecasts with behavioral finance principles to predict the probability of a significant loss for the capitalization-weighted benchmark index. When the predicted probability of loss is low, we close the gap between the beta of the defensive low-volatility portfolio and the capitalization-weighted benchmark by applying leverage. This approach enhances returns and mitigates market dependence. However, when the predicted probability of loss is high, we revert to the defensive beta or hedge market exposure to preserve the downside resilience of low-volatility portfolios. Our results demonstrate that a dynamic approach is more effective than maintaining a fixed target beta of one as it minimizes underperformance in rising markets while retaining the defensive advantages of low-volatility during downturns. We focus in our study on European markets.

The next section details the data and methodology used to construct a low-volatility portfolio and highlights its typical characteristics in comparison to the capitalization-weighted benchmark. Section three outlines our approaches for dynamically managing the market beta of low-volatility portfolios, while section four presents empirical results and discusses the associated observations. Finally, section five reports concluding remarks.

2. THE LOW-VOLATILITY EFFECT

This section outlines the data and methodology used to construct a low-volatility portfolio and summaries the key risk- and return- characteristics of the low-volatility effect. While low-volatility portfolios can be designed in various ways and definitions, including considerations of specific benchmark-related constraints such as sector-, country-, or tracking-error limitations, or by applying additional optimization techniques, we employ a straightforward approach, as the primarily focus of this whitepaper is on using a defensive portfolio for which we can actively manage its beta to the capitalization-weighted benchmark.

The investment universe consists of the 600 largest stocks by market-capitalization in developed European markets. Stocks are ranked within each sector individually according to the inverse of their volatility, calculated as the inverse of standard-deviation of price-returns over the last 250 trading-days. We select from each sector the 10 stocks with lowest volatility to avoid concentration in only very few sectors. We use FactSet's sector definitions, which categorize the investment universe into 12 sectors. This selection process results in a portfolio of 120 stocks, representing 20% of the initial investment universe. The final portfolio composition is weighted according to the inverse volatility of each selected stock and rebalancing is done quarterly in March, June, September, and December. The period of analysis spans from March 2008 to October 2024.

Table 1 confirms the typical characteristics of the low-volatility effect described earlier. The low-volatility portfolio outperforms the capitalization-weighted benchmark by 2.13% annually and displays a reduced annualized volatility of 14.70%, comparing to 18.43% of the benchmark, resulting in a higher Sharpe-ratio of 0.52 versus 0.30 for the benchmark. Further, the maximum drawdown is reduced and amounts 40.91% for the low-volatility portfolio and 51.45% for the benchmark. **Table 1** reveals that the low-volatility portfolio has a beta of only 0.76 and is therefore less sensitive to its capitalization-weighted benchmark.

When examining performance during upside- and downside-markets, the low-volatility portfolio achieves an annualized relative return of -2.50% during upside markets and +9.21% during downside markets. Our results demonstrate the conditional nature of the low-volatility effect, as the strategy effectively reduces negative returns during downside markets, while underperform the market during upside periods. This effect introduces an implicit bet on whether the investment horizon will incorporate more upside or downside market periods. Hence, it might be favorable to adjust the negative relative performance during upside markets while keeping the defensive benefits during downside markets. The figures further confirm that, although all risk metrics can be reduced by the low-volatility portfolio, it can still exhibit relatively high absolute levels , with the 95th percentile high-volatility measure reaching 18.81% in our sample.

In summary, the low-volatility portfolio exhibits higher risk-adjusted returns, reduced tail risk, and lower market sensitivity. However, it also comes with lower returns in upside markets and still relatively high absolute volatility during periods of market stress. In the next section, we aim to address both challenges while preserving the core benefits of the low-volatility factor.

TABLE 1
Performance metrics for the simulated low-volatility portfolio, measured in gross total returns, alongside the performance of broad European equity markets (Benchmark) as represented by the MSCI Europe gross total return index. The currency for both strategies is the Euro, and the analysis period spans from March 5, 2008, to October 31, 2024. For the 95th Percentile high-volatility, we compute the one-year rolling volatility series for each strategy and report the value corresponding to the 95th percentile. For the relative upside & downside market statistics, the benchmark sample is divided into quarters with positive (upside) or negative (downside) returns. Corresponding relative statistics are then calculated for each upside or downside market period and reported in annualized terms.

Source:
The sources of data are FactSet, Bloomberg and own calculations.

	Benchmark	*Low-Volatility*
Annualized return	6.02%	8.15%
Annualized relative return	—	2.13%
Sharpe ratio	0.30	0.52
Annualized volatility	18.43%	14.70%
95th Percentile High-Volatility	22.73%	18.81%
Tracking-error (ex-post)	—	6.53%
Information-ratio	—	0.33
Maximum drawdown	51.45%	40.91%
Relative upside market return	—	-2.50%
Relative downside market return	—	9.21%
CAPM beta (ex-post)	1.00	0.76

3. DYNAMICALLY LEVERAGING LOW-VOLATILITY

The literature has partially addressed the importance of managing the market beta gap in strategies with a beta below one. Amenc et al. (2018) illustrate that the equity risk premium is the primary driver of returns and volatility in a long-only multi-factor portfolio. They note that multi-factor portfolios often have a beta well below one and leaving the beta unmanaged introduces dependence on market conditions and leads to lower long-term returns, as part of the equity risk premium is left on the table. Applying leverage to boost the market-beta of a multi-factor portfolio to one, significantly improves returns but also increases volatility, achieving a similar Sharpe-ratio comparing to an unadjusted multi-factor portfolio. Blitz et al. (2024) specifically focuses on low-volatility portfolios and suggest that leveraging to bring the beta to one, combined with additional risk management techniques to control tracking-error, can improve returns and align the low-volatility portfolio's risk profile more closely with the broader market. Van der Linden et al. (2024) follow a similar approach and test different variations of levered low-volatility portfolios.

The studies achieve promising results by targeting a constant beta of one using leverage which leads to a boost in returns of a defensive strategy but also an increase in risk. Instead of targeting a constant beta of one, this whitepaper proposes the application of a dynamic approach that applies leverage to a low-volatility portfolio only when the probability of a significant loss is low and removes the leverage or even hedge the market-beta of a low-volatility portfolio when the probability of a significant loss is high.

We analyze three scenarios. First and similar as in Blitz et al. (2024) and van der Linden et al. (2024), we continuously target a market beta of one for our low-volatility portfolio, which strategy will also serve as benchmark for the proposed dynamic approaches. Next, we test a strategy that maintains full investment in the low-volatility portfolio, only adjusting leverage to achieve a target beta of one when our signal indicates favorable conditions and reduces the leverage when higher risk is expected. Finally, we examine an even more dynamic approach in which the target beta of our low-volatility portfolio is adjusted according to the exposure level recommended by our model for estimating the probability of a significant loss (detailed in the next subsection). This approach allows not only for the application of leverage but also for hedging market beta, potentially reducing it to zero in certain scenarios.

3.1 ESTIMATING THE PROBABILITY OF A SIGNIFICANT LOSS

To evaluate overall equity market conditions and determine whether the market is trending upward or facing a heightened risk of decline, we developed an equity exposure model[1]. This model provides a risk indicator that estimates the probability of significant losses for the capitalization-weighted benchmark index. Low and decreasing probability of a significant loss signals favorable market environment and high equity exposure, whereas high probability of a significant loss indicates increasing risk and recommends scaling down the equity exposure. The model combines supervised machine learning models to assess relationships among a broad data set while accounting for a behavioral component including trend- and volatility analysis. The machine learning (ML) component follows a model pooling approach, which combines multiple algorithms like support vector classifiers, logistic regression with a regularization penalty, decision trees, neural networks or extreme gradient boost classifier. A model pooling approach leads to a more robust forecast of significant probability of losses through the diversification of multiple algorithms.

The ML model learns from a broad set of data including macro fundamental, price, cross asset and sentiment data to identify complex nonlinear patterns substantial for equity market assessment. With ML as a data driven approach, a relatively long data history must be used for setting up the models and training. Therefore, the out-of-sample period was limited to the last 10 years (starts in 2014). The model estimates the probability of significant loss, which is used to determine four equity investment exposure levels: 0%, 50%, 75%, and 100%. These exposure levels are used to dynamically set a target beta and guide the dynamic application of leverage to low-volatility portfolios as outlined in more detail in the following sections.

3.2 FIXED TARGET BETA OF ONE (FTB-one)

First, we aim to replicate the previous evidence by Blitz et al. (2024) by leveraging the market beta of the low-volatility portfolio to a fixed target of one. This approach is also used to benchmark the two proposed dynamic beta adjustment methodologies to verify its added value. A key factor in managing the beta of the low-volatility portfolio is, unsurprisingly, its own beta relative to the benchmark. We estimate the required level of leverage weekly, based on the market beta of the low-volatility portfolio, rather than assuming a fixed amount of leverage derived ex-post. Since the low-volatility portfolio is rebalanced quarterly, its composition changes frequently, meaning that relying on the historical time-series beta of the entire portfolio would not accurately reflect the portfolio's actual market exposure at any given point. To address this, we first calculate the beta of each individual holding and then aggregating these by taking a weighted average, using the corresponding portfolio weights for each holding. To enhance the stability of beta estimates, we apply the Blume adjustment, as outlined in Blume (1971). We refer to this strategy in the following sections as low-volatility FTB-one.

For implementing leverage or hedging, we use index futures due to their cost-effectiveness, high liquidity, and ability to be traded daily in significant volumes. These instruments also allow us to efficiently hedge market beta by shorting the corresponding capitalization-weighted index at any point in time without having to deal with variation in funding costs or liquidity as it is the case for shorting individual stocks. Similar as in Blitz et al. (2024), we subtract 20bps per year on futures positions to account for any costs associated with usage of index-futures such as

1) For more information, please refer to Čumova & Kremer (2023) under the following link: www.la-francaise systematiam.com/fileadmin/news/marktkommentar/20230620_LaF_Machine_Learning_ DE_FINAL_neu.pdf

trading costs and slippage. The exposure applied to the index-futures is derived as follows:

$$W_t^{(F,\ FTB-one)} = \frac{1}{\beta_{LowVolatility,t}} - 1$$

By employing the ratio of the target beta (set to 1 in the numerator) to the market beta of the low-volatility portfolio, rather than taking the difference between the target beta and the portfolio beta as the weight for index futures, we achieve a slightly higher ex-post beta that aligns more closely with the target of 1. However, using the difference as the weight for index futures leads to similar performance. While our primary objective is to achieve a beta of 1, we also prioritize maintaining leverage at an acceptable level. To this end, we limit leverage to a maximum of 130%, capping the allocation to index futures at no more than 30%. Consequently, the final allocation to index futures is determined as follows:

$$W_t^{(F,\ FTB-one)} = \min(W_t^{(F,\ FTB-one)}, \quad 30\%)$$

3.3 DYNAMICALLY MANAGING BETA GAP (DMB-GAP)

We now turn to our first case for dynamically managing the market beta of low-volatility portfolios. Initially, our objective is to only address the difference between the beta of the capitalization-weighted benchmark, which is one, and the lower beta of the low-volatility portfolio. We call this difference market beta gap. The first case seeks to achieve a market beta of one, when probability of significant loss is low indicated by our model from 3.1 with 100% exposure. When market conditions become less favorable, the approach gradually reduces the exposure to index futures, reverting to the market beta of the low-volatility portfolio without any leverage. This framework avoids any short positions and always maintains a 100% allocation to the low-volatility portfolio. Instead, it either levers the beta up to one, or removes the overlay, allowing the portfolio to utilize the defensive beta in times where it is mostly needed. We refer to this strategy in the following sections as low-volatility DMB-Gap. The weight applied to the index-futures is derived as follows:

$$W_t^{(F,\ DMB-Gap)} = \frac{1}{1-(1-\beta_{LowVolatility,t}) \times exposure_t} - 1, \text{ where } exposure \in \{1, 0.75, 0.5, 0.25, 0\}$$

Similar as before, we limit the use of leverage to a maximum of 130% and hence the allocation to index futures is set to a maximum of 30%.

$$W_t^{(F,\ DMB-Gap)} = \min(W_t^{(F,\ DMB-Gap)}, \quad 30\%)$$

3.4 DYNAMICALLY MANAGING BETA (DMB)

Our second case emphasizes the dynamic management of the overall market beta of the low-volatility portfolio, extending beyond just addressing the market beta gap. This strategy employs leverage to align the low-volatility portfolio's market beta with one when the probability of significant loss is low. When the probability of significant loss increases, the portfolio's exposure to the market is gradually reduced, potentially reaching zero in certain scenarios. To achieve this, the strategy incorporates shorting index futures while consistently maintaining the allocation to the low-volatility portfolio, effectively hedging its exposure to the broader equity market. As previously defined in Section 3.1, our model for predicting the probability of significant losses returns exposure levels in four discrete steps, ranging from 0% to 100% in 25% increments. We use this information to set the target beta of our low-volatility portfolio according to these levels. Therefore, a 100% exposure corresponds to a target beta of 1, which requires leverage. A 75% exposure targets a beta of 0.75, which generally requires little to no adjustment. A 50% exposure targets a beta of 0.50, for which shorting index futures is necessary. To implement leverage, we use the same approach as in section 3.2, dividing the target beta by the current beta of the low-volatility portfolio. This method results in a realized beta that more closely aligns with the target beta. For hedging, however, we use the difference between the suggested exposure level and the beta of the low-volatility portfolio to ensure that no net short positions are taken against the benchmark index. We refer to this strategy in the following sections as low-volatility DMB. The allocation to index-futures is defined as follows:

$$W_t^{(F,\ DMB)} = \begin{cases} \dfrac{exposure_t}{\beta_{LowVolatility,t}} - 1, & if\ exposure_t > \beta_{LowVolatility,t} \\ exposure_t - \beta_{LowVolatility,t}, & if\ exposure_t \leq \beta_{LowVolatility,t} \end{cases}$$

$$where\ exposure_t \in \{1, 0.75, 0.5, 0.25, 0\}$$

Once again, we impose a leverage limit of 130%, capping the allocation to index futures at a maximum of 30%.

$$W_t^{(F,\ DMB-Gap)} = \min(W_t^{(F,\ DMB-Gap)},\quad 30\%)$$

4. EMPIRICAL RESULTS

Table 2 presents the empirical results for the standard low-volatility portfolio, the low-volatility FTB-one portfolio and the newly proposed low-volatility DMB-Gap and low-volatility DMB strategies. Limited by the availability of out-of-sample predictions from our exposure management model as discussed in Section 3.1, the analysis period spans from January 2014 to October 2024. The performance of the low-volatility portfolio aligns with the patterns observed in Table 1, although its annualized return is slightly lower than that of the capitalization-weighted benchmark (7.05% vs. 7.16%). However, the portfolio demonstrates superior risk metrics, including lower volatility (11.94% vs. 15.98%) and a reduced maximum drawdown (27.24%

vs. 35.23%), leading to a higher Sharpe ratio of 0.56 compared to the benchmark with 0.42. Further, the pattern during upside- and downside-markets remains the same, namely relative underperformance of -4.69% during upside markets and relative outperformance of +8.91% during downside-markets.

Comparing the standard low-volatility portfolio with low-volatility FTB-one, the latter delivers a significant improvement in annualized returns, increasing by over 1.10% relative to the standard low-volatility portfolio. Another improvement that the low-volatility FTB-one strategy achieves is the symmetry in upside and downside markets. Instead of relative underperformance during upside markets, we see now even a slight outperformance of +0.09% during upside markets and outperformance of +3.0% during downside markets. Hence, continuously targeting a beta of one achieves the reduction of the conditionality of the standard low volatility portfolio and brings the overall profile of the portfolio closer to the benchmark, which is also confirmed by the lower tracking-error of 3.42%, comparing to a tracking-error of 5.59% for the standard low-volatility portfolio. Nevertheless, consistent with findings from previous studies, the enhanced returns come at the cost of increased volatility (15.45% vs. 11.94%) and a higher maximum drawdown (35.64% vs. 27.24%) comparing to the standard low-volatility portfolio, aligning its risk profile more closely with that of the capitalization-weighted benchmark. As a result, while the strategy generates higher returns, it significantly diminishes the defensive benefits of the low-volatility portfolio, as also reflected by the lack of improvement in the Sharpe ratio.

Next, we discuss the empirical results of our low-volatility DMB-Gap strategy. Comparing the annualized returns of the low-volatility DMB-Gap strategy with those of the standard low-volatility portfolio, we observe a significant improvement of 1.41% in annualized returns. This also represents an additional gain of 0.30% over the annualized return generated by the low-volatility FTB-one strategy. While the DMB-Gap strategy delivers even higher returns than the fixed target beta approach, it simultaneously reduces annualized volatility, achieving a level of only 13.90% compared to 15.45% for the low-volatility FTB-one portfolio. By dynamically managing the market-beta gap instead of maintaining a constant target beta of one, the DMB-Gap strategy not only enhances returns but also limits the increase in volatility. The low-volatility DMB-Gap strategy achieves a Sharpe ratio of 0.58, outperforming both the low-volatility FTB-one portfolio by 16% (from 0.50) and the standard low-volatility portfolio by 3.6% (from 0.56). Moreover, extreme risk measures such as maximum drawdown and 95% high-volatility are significantly reduced when compared to the low-volatility FTB-one portfolio (29.27% vs 35.64% and 16.79% vs 19.61%), aligning the risk-profile of the DMB-Gap strategy more closely with the standard low-volatility portfolio instead of that of the capitalization-weighted benchmark.

Examining the relative performance during different market environments, the DMB-Gap strategy exhibits a slightly negative relative performance of -1.24% in upside markets, which represents still a notable improvement over the standard low-volatility portfolio's underperformance in upside markets of -4.69%, relative to the benchmark. Further, the DMB-Gap strategy still achieves a pronounced outperformance of +6.40% in downside markets. Finally, while leverage is applied to increase the strategy's beta toward one, the realized beta is only 0.84. This is higher than the beta of the standard low-volatility portfolio but lower than that of the fixed target beta approach, indicating that some of the defensive benefits remain intact.

We now turn to the second case of dynamically leveraging the low-volatility effect: the low-volatility DMB strategy. The low-volatility DMB strategy delivers the highest annualized returns in our sample as it outperforms the benchmark by 1.54%, the standard low-volatility portfolio by 1.65% and the low-volatility FTB-one portfolio by 0.54%. Furthermore, this strategy achieves the lowest level of volatility among all alternatives, with a volatility level of 11.31%, which is even below the level of the standard low-volatility portfolio (11.94%). As a result, the low-volatility DMB strategy boasts the highest Sharpe ratio at 0.74, representing a significant improvement. Specifically, it enhances the Sharpe ratio of the benchmark by 76% (from 0.42), the standard low-volatility portfolio by 32% (from 0.56) and the low-volatility FTB-one portfolio by 48% (from 0.50). Further, extreme risk measures are lowest among all other portfolios where maximum drawdown is only 13.92% comparing to 35.23% for the benchmark and 27.24% for the standard low-volatility portfolio. 95% high-volatility is also lowest among all other portfolios with a value of only 12.98% comparing to 20.33% for the benchmark, 14.41% for the standard low-volatility portfolio and 19.61% for the low-volatility FTB-one portfolio.

The results for relative performance during upside- and downside markets are slightly striking as conditionality is even increased comparing to the standard low-volatility portfolio. The low-volatility DMB strategy exhibits a negative relative performance of -5.80% in upside markets. This effect may arise because the target beta doesn't immediately return to 1 after a drawdown, causing it to partially miss periods of recovery. In contrast, the DMB strategy achieves a pronounced outperformance of +10.75% in downside markets. Hence, hedging market beta helps to reduce peak values of risk measures and offers additional protection during periods of market stress. Finally, while leverage is partly applied to increase the strategy's beta toward one, the realized beta is only 0.50 which supports the effectiveness of our model for exposure management.

TABLE 2

Table 2 reports empirical results on capitalization-weighted benchmark which is the MSCI Europe Gross Total Return Index, the low-volatility portfolio constructed as outlined in section 2 and the proposed versions including fixed target beta and dynamically adjusted target beta including DMB-Gap and DMB. The currency for all strategies is Euro, all figures based on gross total returns and the analysis period spans from January 3, 2014, to October 31, 2024. For the 95th Percentile high-volatility, we compute the one-year rolling volatility series for each strategy and report the value corresponding to the 95th percentile. For relative upside & downside market statistics, the benchmark sample is divided into quarters with positive (upside) or negative (downside) returns. Corresponding statistics are then calculated for each upside or downside market period and annualized.

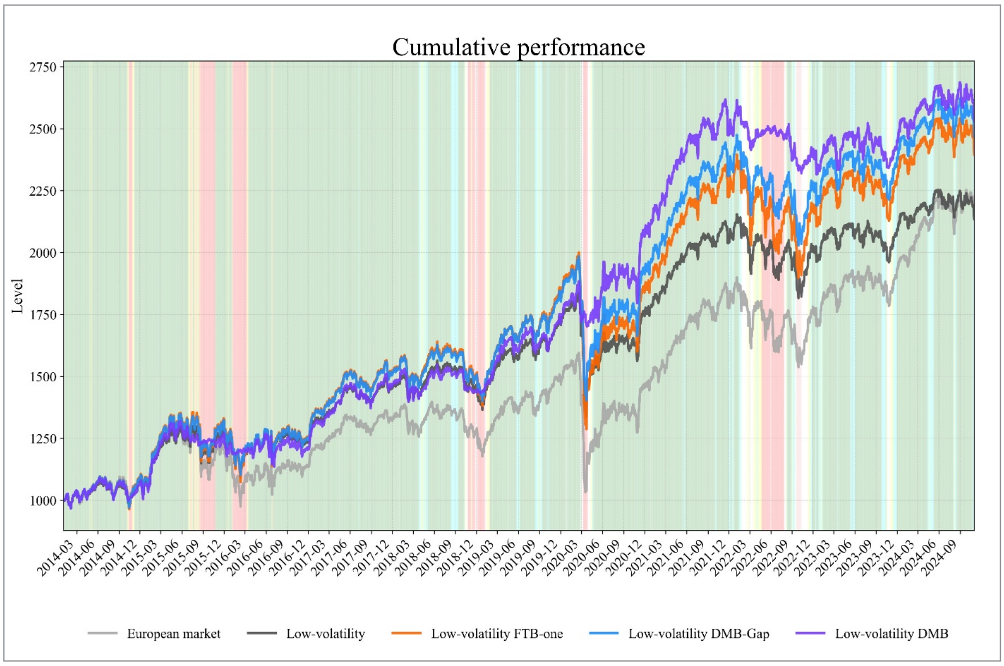
Source:
The sources of data are FactSet, Bloomberg and own calculations.

	Benchmark	*Low-volatility*	*Low-volatility FTB-one*	*Low-volatility DMB-Gap*	*Low-volatility DMB*
Annualized Return	7.16%	7.05%	8.16%	8.46%	8.70%
Annualized Relative Return	—	-0.11%	1.00%	1.30%	1.54%
Sharpe Ratio	0.42	0.56	0.50	0.58	0.74
Annualized Volatility	15.98%	11.94%	15.45%	13.90%	11.31%
Sortino Ratio	0.52	0.70	0.61	0.74	0.95
95th Percentile High-Volatility	20.33%	14.41%	19.61%	16.79%	12.98%
Ex-post Tracking Error	—	5.59%	3.42%	4.43%	11.22%
Ex-post Information Ratio	—	-0.02	0.29	0.29	0.14
Maximum Drawdown	35.23%	27.24%	35.64%	29.27%	13.92%
Relative Upside Market Return	—	-4.69%	0.09%	-1.24%	-5.80%
Relative Downside Market Return	—	8.91%	3.00%	6.40%	16.82%
Ex-post CAPM Beta	1.00	0.72	0.95	0.84	0.50
Ex-post CAPM Alpha	—	1.27%	0.93%	1.84%	4.58%

FIGURE 1

Figure 1 displays the cumulative performance series for the standard low-volatility portfolio, low-volatility FTB-one, low-volatility DMB-Gap and low-volatility DMB portfolios. The period spans from January 3 2014 to 31. October 2024. The background color represents the different exposure levels derived from our model described in section 3.2. Green indicates 100% exposure, blue 75%, yellow 50%, white 25% and red equals to 0% exposure

Source:
The sources of data are FactSet, Bloomberg and own calculations.



After discussing the figures from Table 2, it is also valuable to visually assess the behavior of each strategy during periods of market stress. Figure 2 illustrates the one-year rolling volatility series for each strategy under consideration. The background color represents the different exposure levels derived from our model. Green indicates 100% exposure, blue 75%, yellow 50%, white 25% and red equals to 0% exposure. The low-volatility FTB-one portfolio consistently demonstrates the highest levels of volatility and behaves very similar as the capitalization-weighted benchmark, particularly during stress events such as in 2016, 2020, and early 2022. These pronounced volatility spikes highlight the trade-off inherent in this approach, where increasing market beta towards one enhances returns, but also amplifies sensitivity to market downturns. Consequently, the low-volatility strategy with steady target beta consistently elevates volatility and diminishes the defensive benefits during times of market stress, particularly when compared to the standard low-volatility portfolio.

In contrast, the low-volatility DMB-Gap and low-volatility DMB strategies offer a more effective balance between risk and returns. The low-volatility DMB-Gap strategy achieves a level of volatility slightly higher than the standard low-volatility portfolio but considerably lower than the fixed target beta strategy, particularly during periods of market stress. For example, in June 2016, the fixed target beta strategy recorded a one-year rolling volatility of 23.3%, compared to 20.4% for the DMB-Gap strategy. Similarly, during the COVID-19 crisis in early 2020, volatility reached 27.1% for the low-volatility FTB-one portfolio versus 23% for the DMB-Gap strategy. By November 2022, the volatility levels were 19.3% for the low-volatility FTB-one strategy, compared to a more moderate 15.8% for the DMB-Gap approach.

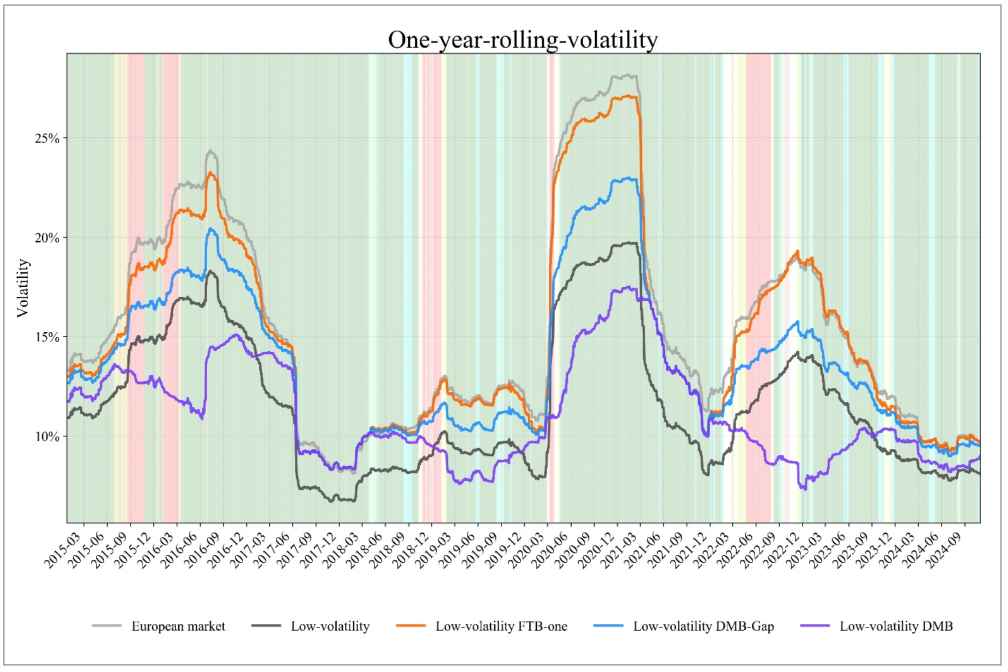
Thus, while the DMB-Gap strategy achieves higher overall returns as reported in Table 2, it effectively reduces the volatility increases associated with leverage, particularly during periods of market stress.

The low-volatility DMB strategy, in contrast, exhibits a more dynamic behavior. Its volatility can occasionally exceed that of the standard low-volatility portfolio when the target beta is set to one, but it can also fall significantly below the standard portfolio's volatility when the target beta is reduced, achieved through shorting index futures. For instance, in June 2016, the standard low-volatility portfolio recorded a one-year rolling volatility of 18.3%, compared to a lower 14.5% for the DMB strategy. Similarly, during the COVID-19 crisis in early 2020, the standard portfolio's volatility rose to 19.7%, while the DMB strategy maintained a more moderate 17.5%. By November 2022, the standard portfolio's volatility stood at 14.2%, whereas the DMB strategy achieved an impressively low 8.6%. However, in periods of upward-trending markets, such as June 2017 and from May to December 2021, all leveraged strategies displayed identical volatility levels. This occurred because our signal implied a 100% exposure, resulting in a target beta of one for both dynamic strategies. During these periods, the strategies were fully benefiting from increased exposure, while still preserving the defensive attributes of the low-volatility factor during more turbulent times when defensiveness proved most valuable, which is a clear benefit comparing to the low-volatility portfolio with steady-leverage. Figure 3 in the appendix illustrates the maximum drawdown series, where a similar pattern can be observed.

FIGURE 2

Figure 2 displays the one-year rolling volatility series for the standard low-volatility portfolio, low-volatility FTB-one portfolio, low-volatility DMB-Gap and low-volatility DMB portfolios. The period spans from 23. December 2014 to 31. October 2024. The background color represents the different exposure levels derived from our model described in section 3.1. Green means 100% exposure, blue 75%, yellow 50%, white 25% and red 0% exposure respectively.

Source:
The sources of data are FactSet, Bloomberg and own calculations.



5. CONCLUSION

In this whitepaper, we introduce an innovative approach to capturing the low-volatility premium by addressing its lower market beta to the capitalization-weighted benchmark, which can lead to periods of underperformance in bullish markets. By targeting a fixed beta of one for a low-volatility portfolio, we achieve higher realized returns, but this also increases the portfolio's risk profile, aligning it more closely with the broad market and elevating volatility and tail risk measures. While enhancing returns is an appealing objective, preserving the defensive qualities of an unlevered low-volatility portfolio—especially during market downturns—remains a key appeal for many investors. Our empirical results confirm that low-volatility portfolios generally underperform in strong bull markets but excel during market declines. By dynamically managing market beta—adjusting it when the unlevered portfolio struggles to keep pace with the market while capitalizing on its defensiveness during periods of market stress—we can enhance returns without significantly increasing risk. This approach results in ex-post risk metrics that are close to those of the standard low-volatility portfolio while significantly enhance returns. We demonstrate that this strategy already yields promising results with a relatively simple portfolio construction approach and can be further improved by additional design choices for constructing low-volatility portfolios.

Our results demonstrate that the proposed low-volatility DMB-Gap portfolio allows low-volatility investors to participate more efficiently in upside markets while still benefiting from the defensive advantages of the low-volatility portfolio during periods of market stress. Thus, prioritizing higher total returns does not necessarily entail diminishing the positive defensive characteristics of low-volatility, which is a clear added value to low volatility with constant target beta of one. Additionally, the low-volatility DMB strategy offers even more defensive characteristics, enabling investors to capture gains in rising markets while significantly reducing tail risks and volatility, all while maintaining full exposure to the low-volatility portfolio. The proposed methodologies are not limited to low-volatility portfolios only, and can also be applied to multi-factor portfolios, which typically have a market beta of less than one.

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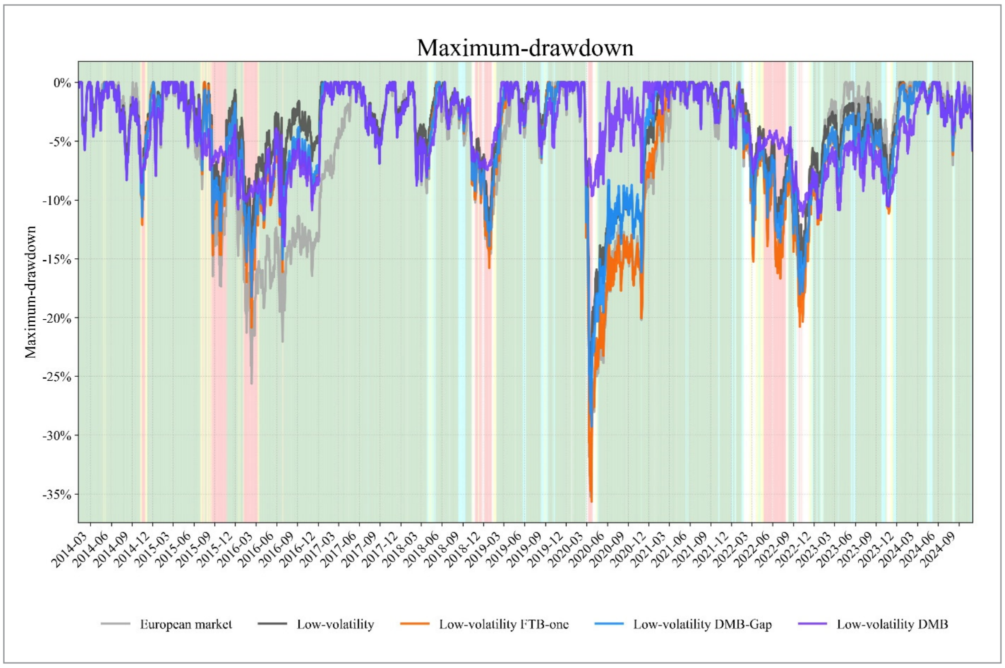
7. APPENDIX

FIGURE 3

Figure 3 displays the maximum-drawdown series for the standard low-volatility portfolio, low-volatility FTB-one, low-volatility DMB-Gap and low-volatility DMB portfolios. The period spans from 3. January 2014 to 31. October 2024. The background color represents the different exposure levels derived from our model described in section 3.2. Green means 100% exposure, blue 75%, yellow 50%, white 25% and red means 0% exposure

Source:
The sources of data are FactSet, Bloomberg and own calculations.



Do you have any further questions? – We are pleased to help you.

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